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Monetary Dynamics and Inflation Persistence: A Machine Learning Approach Applied to Turkey

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Abstract

This study re-assesses the root causes of inflation through an innovative hybrid analytical framework integrating deep neural networks, random forest algorithms, and causal inference (DoWhy) within the Quantity-Theoretical Inflation Theory, using monthly data from Turkey for the period 2003M05–2025M01. The findings reveal that inflation expectations and exchange rate fluctuations are the most influential drivers of inflation, overshadowing other variables such as money supply, real interest rates, and global oil prices. Although the exact ordering of predictors is model dependent, and the random forest assigns the leading role to the real interest rate, the signal shared across all three methodological pathways rests on expectations and the exchange rate. While money supply growth aligns with monetarist theory and remains a consistent source of upward price pressure, its impact is often mediated through expectations and currency depreciation. Causal estimates confirm that Turkey's persistent inflation is fueled not just by macroeconomic imbalances but by the erosion of policy credibility and weak anchoring of expectations, particularly after 2017. The study contributes methodologically by introducing AI-powered modeling to inflation analysis in emerging markets, and empirically by validating the central role of expectations and exchange rate pass-through in a structurally fragile, import-dependent economy. The results suggest that sustainable price stability in Turkey hinges on reestablishing central bank independence, adopting orthodox inflation targeting, and regaining public trust through consistent and transparent communication.

Keywords: inflation theory; emerging markets; machine learning time series analysis; random forest

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1. Introduction

Inflation is inherently complex, and this complexity contributes to persistent uncertainty regarding both its causes and the extent to which it can be explained. This issue is particularly acute in emerging markets, where the adverse economic and social effects of inflation are deeply felt (see Bick, 2010; Yilmazkuday, 2011, 2022). While many emerging economies have managed to reduce inflation through sound monetary frameworks, Turkey continues to struggle with high and volatile inflation. As of 2024, Turkey holds the second-highest inflation rate among emerging markets after Argentina, marking a structural divergence from global trends.

Understanding Turkey's inflation dynamics requires a historical perspective, as price instability has been a recurring feature of the economy. From the early 1940s onward, Turkey's

inflationary trajectory can be divided into distinct phases shaped by external shocks, fiscal dynamics, and monetary policy regimes. The wartime economy (1939–1969) was marked by monetary expansion and global supply shocks, especially during World War II and the 1958 crisis (Akyıldız & Eroğlu, 2004; Arslan, 2016). The 1970s brought global oil shocks, the Cyprus conflict, and political fragmentation, pushing inflation above 60% (Koçak et al., 2017; Yıldırım & Engeloğlu, 2023). The period from 1980 to 2001 was characterized by chronic high inflation and financial instability, despite market-oriented reforms. A significant improvement came between 2002 and 2016, as inflation targeting and IMF-backed stabilization programs brought price stability (Arpac & Bird, 2009; Yeldan, 2011). However, beginning in 2017, heterodox monetary policies, declining central bank independence, and global shocks such as COVID-19 reignited inflationary pressures, leading to a resurgence of double-digit inflation. As of December 2024, the annual inflation rate stood at 44.38%.

Figure 1 provides a visual overview of Turkey's inflationary path between 1939 and 2025, highlighting periods of price stability and volatility. Historical evidence underscores the importance of structural reforms, credible monetary policy, and resilience against external shocks for maintaining long-term price stability.

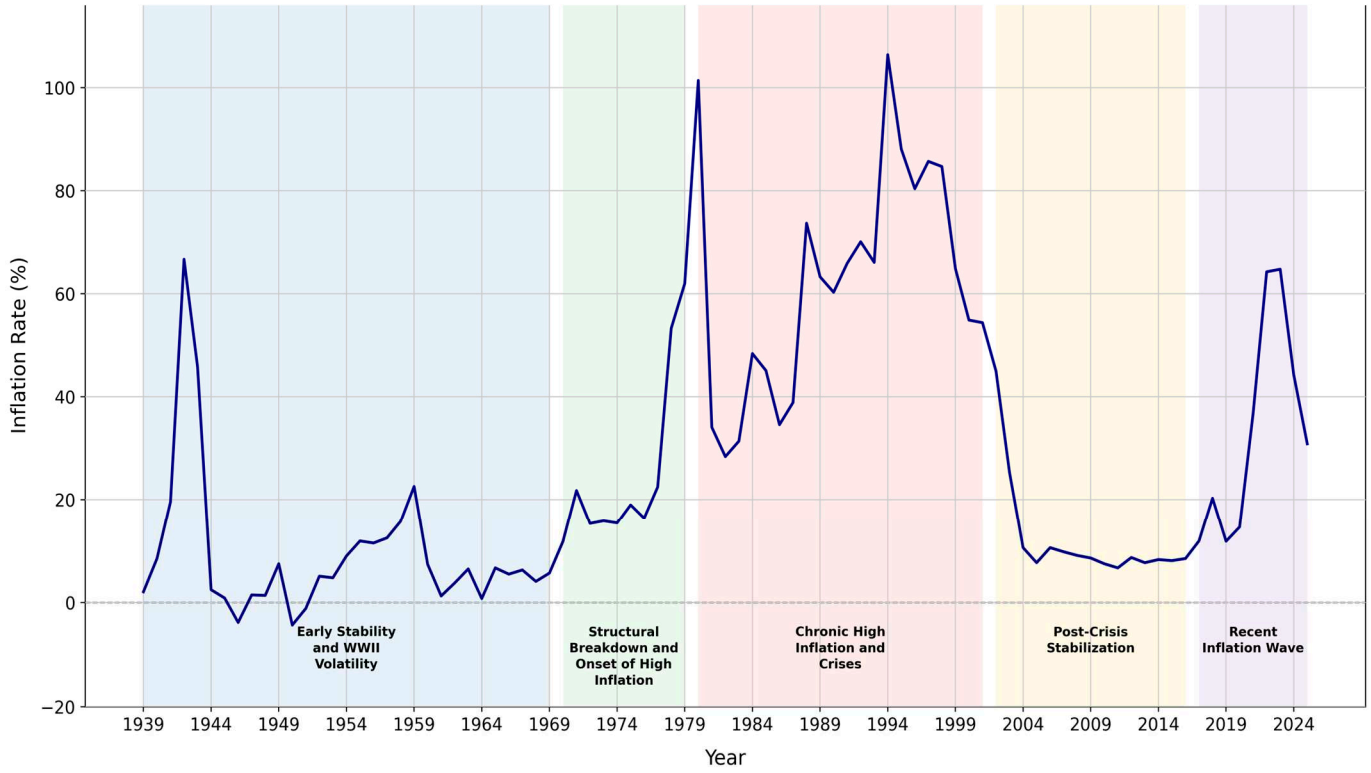

Figure 1. The inflationary evolution in Turkey (1939–2025).

The inflationary trajectory in Turkey over the past century reveals a complex interplay among various macroeconomic variables, including money supply growth, budget deficits, exchange rates, economic growth, real interest rates, balance of payments dynamics, import price growth, and global energy prices. Each of these factors has played a pivotal role in shaping inflationary outcomes, with global energy price fluctuations emerging as a particularly influential driver, especially during periods of oil price shocks.

Empirical studies examining inflation dynamics in Turkey have consistently highlighted the roles of fiscal dominance (Metin, 1998; Erkam & Çetinkaya, 2014; Koyuncu, 2014; Kaya & Öz, 2016; İpek & Akar, 2016; Şahin, 2019; Maraş & Dumrul, 2019; Karadeniz, 2022; Karaş, 2023; Emek, 2024), monetary policy credibility (Tekin-Koru & Özmen, 2003; Cesur, 2006; Özmen & İdil Koçak, 2012; Bozkurt, 2014; Gocmen, 2016; İslatince, 2017; Kılavuz &

Altınöz, 2020; Turna & Özcan, 2021; Emeç, 2023; Korkmaz, 2023; Torun et al., 2024; Ersin, 2025), exchange rate pass-through (Kara & Öğünç, 2008; Çatık & Güçlü, 2012; Benk & Kösekahyaoğlu, 2019; Altunöz, 2020; Karaoğlu & Demirel, 2021; Bilgili et al., 2022; Felıx, 2022; Şeker, 2022; Türel & Orhan, 2022; Asfuroglu et al., 2023; Bilgili et al., 2024), and structural rigidities (Cizre-Sakaallioglu & Yeldan, 1999; Erlat, 2002; Ertuğrul & Yeldan, 2003; Boratav & Yeldan, 2006; Kara & Küçük-Tuğer, 2010) in explaining the persistence of inflation. The historical evidence presented in this study aligns with these findings, demonstrating that episodes of chronic inflation were often rooted in institutional weaknesses and policy inconsistency.

Despite numerous stabilization efforts, Turkey's inflationary problem remains unresolved. The persistence of high inflation reflects a complex interplay of macroeconomic, institutional, and behavioral factors—including monetary expansion, weak policy credibility, inflation expectations, exchange rate dynamics, and external vulnerabilities. Accordingly, this study revisits the core determinants of inflation in Turkey by combining a monetarist theoretical foundation with a cutting-edge machine learning framework.

The main objective is to re-evaluate inflation dynamics under the lens of Quantity-Theoretical Inflation Theory (QTIT) using a novel Composite Machine Learning Time Series Analysis (CMTSA) approach. The contributions of this study are threefold: (i) It introduces artificial intelligence tools, such as deep neural networks and causal inference, to the inflation literature on Turkey; (ii) It provides a structured understanding of the evolving importance of inflation determinants across time; and (iii) It evaluates the efficacy of orthodox versus heterodox monetary strategies. The next sections develop the theoretical model, detail the data and methodology, and present empirical results, culminating in policy implications and suggestions for future research.

2. Theoretical Background

The results of implementing anti-inflationary policies in many countries worldwide, when analyzed over a sufficiently long period, largely confirm the quantity theory of inflation's proposition that inflation is a monetary phenomenon (Grauwe & Polan, 2005; Focacci & Focacci, 2024). This is the basis of perhaps the most famous and often quoted statement by Friedman (1994, p. 49): "Inflation is always and everywhere a monetary phenomenon, in the sense that it is and can only be produced by a faster increase in the money supply than in output". The vitality of this proposition lies in the ability of the equation of exchange to be applied, explicitly or implicitly, to ever-changing historical conditions and institutional changes. For Turkey, the co-movement of inflation is also significantly driven by the co-movement of monetary policy (Saygılı, 2023). Graff (2008) derived the quantity theory of inflation, which takes into account the percentage changes (or growth rates) over time of variables in the quantity theory of money. The theory incorporates price determination within the traditional model (Moser, 1995). Accordingly, the model is extended to account for both openness and expectations, thereby enabling an analysis of whether the source of inflation is monetary, cost-push, demand-pull, or structural. In this regard, the model offers a robust theoretical framework for understanding the multifaceted nature of inflation. Consequently, this section of the study derives an inflation function for Turkey based on the mathematical foundations of the quantity theory of inflation.

As it is known, Turkey is a small economy that is open to the outside. In a small open economy, the general level of prices (P) is a weighted average of the prices of domestic goods (P_D) and the prices of imported goods subject to foreign trade (P_M). In this logarithmic form, it can be expressed as follows:

$$\log P = \varnothing(\log P_D) + (1 - \varnothing)(\log P_M) \quad (1)$$

In this equation, $\varnothing$ and $(1-\varnothing)$ represent the weights of domestic and international goods sold in the domestic market, respectively. The price of imported goods (P_M) is determined externally on the world market and is equal in national currency multiplied by the external price level (P^*) and the nominal exchange rate (E), as stated in Equation (2). According to this equality, both the increase in the nominal exchange rate and the increase in the external price level raise the general price level.

$$\log P_M = \log E + \log P^* \tag{2}$$

Assuming that the price of domestic goods (P_D) is determined in the money market and that, for simplicity, the demand for domestic goods moves in parallel with the demand for the economy as a whole, the price of domestic goods is determined by the money market equilibrium condition. The equilibrium condition refers to the situation in which the supply of real money (M^S/P) equals the demand for real money $\left(m^d\right)$. Under this condition, price formation is as shown in Equation (3).

$$\log P_D = \beta\left(\log M^s - \log m^d\right) \tag{3}$$

β is a scale factor that represents the relationship between demand in the economy as a whole and demand for non-tradable goods. The demand for real money $\left(m^d\right)$ is a function of real income (y) and the nominal interest rate (i). The nominal interest rate, on the other hand, is equal to the sum of inflation expectations (π^e) and the real interest rate (r).

$$m^d = f(\underbrace{y}_{+}, \underbrace{r+\pi^e}_{-}) \tag{4}$$

According to the theory of money demand, an increase in real income will increase the demand for money, while an increase in expected inflation will decrease the demand for money. Assuming that prices are shaped by adaptive expectations, where $\Delta\log P_{t-1}$ is the actual inflation rate in the period $t-1$ and π^e_{t-1} is the expected inflation in the period $t-1$, the expected inflation in period t is as in Equation (5):

$$\pi^e_t = \lambda(\Delta\log P_{t-1}) + (1-\lambda)\pi^e_{t-1} \tag{5}$$

Under the adaptive expectations assumption, setting λ = 1 implies that expected inflation is fully determined by the previous period's observed inflation. In this equation, assuming λ = 1, the reduced-form expected inflation equation is obtained. This equation is given in Equation (6). Accordingly, inflation expectations are proxied by lagged inflation in the empirical analysis.

$$\pi^e_t = (\Delta\log P_{t-1}) \tag{6}$$

The log-linear money demand function based on these explanations is as follows:

$$\log m^d_t = \alpha_1\log y_t - \alpha_2\Delta\log P_{t-1} - \alpha_3\log r_t \tag{7}$$

When Equation (7) is substituted into Equation (3), the result is Equation (8).

$$\log P_{D,t} = \beta\left(\log M^S_t - \alpha_1\log y_t + \alpha_2\Delta\log P_{t-1} + \alpha_3\log r_t\right) \tag{8}$$

When Equations (2) and (8) are substituted into Equation (1), the result is Equation (9).

$$\log P = \varnothing\beta\left(logM^S_t - \alpha_1 logy_t + \alpha_2\Delta logP_{t-1} + \alpha_3 logr_t\right) + (1-\varnothing)(logE + logP^*) \tag{9}$$

When the derivative of Equation (9) is taken with respect to time, the quantity theoretical inflation equation is reached.

$$\frac{d(logP_t)}{dt} = \varnothing\beta\left(\frac{d(log\ M_t^S)}{dt} - \alpha_1\frac{d(\log y_t)}{dt} + \alpha_2\frac{d(\pi_t^e)}{dt} + \alpha_3\frac{d(log\, r_t)}{dt}\right) + (1-\varnothing)\left(\frac{d(log\, E)}{dt} + \frac{logP^*}{dt}\right) \quad (10)$$

Equation (11) provides a clearer and more explicit representation of Equation (10) by employing dot notation.

$$\pi = \varnothing\beta\left(\dot{m}^s - \alpha_1\dot{y} + \alpha_2\dot{\pi}^e + \alpha_3\dot{r}\right) + (1-\varnothing)\left(\dot{e} + \dot{p}^*\right) \quad (11)$$

In this inflation function, z is added directly as a shift factor. z represents the cost pressure of global oil prices. As is well known, global factors such as commodity or energy prices are potential external drivers of domestic inflation (Bensenouci & Sahed, 2023). These global factors are particularly important for Turkish inflation because the economy is highly dependent on oil imports and, therefore, oil price increases are an important cost driver for the economy due to oil price pass-through (see Mumtaz & Surico, 2012; Charnavoki & Dolado, 2014; Ha et al., 2023; Kocoglu, 2023). Accordingly, z is included in the model below as a potential additional explanatory variable.

Based on the basic assumptions outlined above, it is possible to make the following a priori assumptions about the signs of the explanatory variables:

$$\pi = f(\underbrace{\dot{m}^s}_{+}, \underbrace{\dot{y}}_{-}, \underbrace{\dot{\pi}^e}_{+}, \underbrace{\dot{r}}_{+}, \underbrace{\dot{e}}_{+}, \underbrace{\dot{p}^*}_{+}, \underbrace{z}_{+}) \quad (12)$$

An increase in the growth rate of the money supply $\left(\dot{m}^s\right)$, the rate of change in expected inflation $\left(\dot{\pi}^e\right)$, the change in the real interest rate $(\dot{r})$, the change in the TL/US dollar nominal exchange rate $(\dot{e})$, growth rate in foreign price level $\left(\dot{p}^*\right)$, growth rate in global oil prices (z) leads to an increase in inflation, while economic growth rate $(\dot{y})$ leads to a decrease in inflation.

3. Data

This study presents a Composite Machine Learning Time Series Analysis (CMTSA) framework to examine the dynamic relationships proposed by the Quantity-Theoretical Inflation Theory (QTIT) in Turkey using monthly data whose raw coverage extends from May 2003 to January 2025. The framework integrates advanced machine learning tools with traditional econometric techniques to capture both linear and nonlinear interactions among key macroeconomic variables. Because the models are estimated on rates of change and the expectations proxy requires lagged information, the initial months of the raw sample are consumed by these transformations, and the estimation dataset comprises 260 monthly observations spanning June 2003 to January 2025 across eight macroeconomic indicators, of which the price level is the modelling target and the remaining seven serve as predictors, covering critical episodes such as the 2008 global financial crisis, the 2018 Turkish currency crisis, and the post-COVID-19 economic shifts.

Table 1 outlines the macroeconomic variables used in the QTIT framework, providing a brief description and their respective data sources.

The descriptive statistics for 2003–2024, displayed in Table 2, illustrate a few striking features that characterize the erratic macroeconomic environment of Turkey, and some regularities can be observed from both centrality and distribution patterns: The price level

is highly volatile; its standard deviation (554.39) is much larger than its mean (443.16), suggesting high inflation episodes that occur over all of the sample period.

Table 1. Macroeconomic variables in the QTIT framework.

Symbol	Variable	Description	Source	Transformation
P	Price Level	Consumer Price Index (CPI)	CEIC Data	Δlog(CPI): monthly inflation; target variable
M	Money Supply	Broad Money Supply (M2, includes cash and deposits)	CEIC Data	Monthly growth rate
Y	Real Gross Domestic Product	Industrial Production Index (proxy for economic output)	CEIC Data	Monthly growth rate
R	Real Interest Rate	Nominal interest rate adjusted for inflation	Author's calc.	Monthly change
E	Nominal Exchange Rate	TL/USD exchange rate	CEIC Data	Monthly rate of change
π^e	Expected Inflation	First difference of the log of the lagged CPI	CEIC Data	Rate of change in the ML models; level form in the causal analysis (Section 5.3)
P^*	Foreign Price Level	Import Price Index	CEIC Data	Monthly rate of change
Z	Global Oil Prices	Brent Crude Oil Price	CEIC Data	Monthly rate of change

Table 2. Descriptive statistics.

Variable	N	Mean	Median	Std Dev	Min	Max	IQR	Skewness	Kurtosis
P	261	443.16	237.18	554.39	99.28	2819.65	263.07	2.63	6.46
π^e	261	1.29%	0.89%	1.78%	−1.44%	13.58%	1.29%	3.21	14.96
Z	261	72.92	71.32	25.72	18.38	132.72	37.73	0.23	−0.79
y	261	5.89%	6.71%	9.01%	−31.46%	66.79%	7.55%	0.72	9.99
P*	261	110.15	106.26	18.25	70.32	157.90	28.58	0.19	−0.57
E	261	5.98	2.12	8.34	1.17	35.46	4.33	2.27	4.18
M	261	2.53 †	0.92 †	3.97 †	0.06 †	17.71 †	1.84 †	2.39	4.93
r	261	7.78%	5.72%	9.45%	−57.44%	67.57%	7.32%	1.23	19.73

Note: The statistics are computed on the level series (261 monthly observations, 2003M05 to 2025M01). The models are estimated on the transformed series described in the Transformation column of Table 1, with an estimation sample of 260 observations. † Values for M are expressed in trillion Turkish lira (TL).

The fact that the middle 50% of observations extends over a broad range, as indicated by the interquartile range of 263.07 points to different inflation regimes from the stabilization period to the recent high inflation episodes. Likewise, the exchange rate is highly volatile, as the Turkish Lira lost value substantially from 1.17 to 35.46 TL/USD, and the IQR of 4.33 already indicates a structural weakness in times of little volatility. Many of the variables are positively skewed, indicating a few very large values. This is especially so in the case of inflation expectations (skewness = 3.21), although their IQR is relatively tight at 1.29%, which indicates the central bank perhaps had some success in anchoring expectations during tranquility.

Money supply pattern exhibits the same asymmetry; this time, the IQR of 1.84 trillion TL reflects the loose monetary policies followed during varying regimes. Very high kurtosis, especially 19.73 for the real interest rate, expresses fat tails and a rather high occurrence of extreme observations, typical for emerging market economies undergoing frequent shocks. Its IQR of 7.32% of the real interest rate shows large variation also in normal times and thus produces a headwind on monetary policy propagation. Interestingly, some of the variables are quite stable in a central range. Economic growth has an IQR of 7.55%; although the

31.46% contraction recorded during the COVID episode is extreme, growth fluctuations in normal times remain moderate.

Brent oil prices exhibit the least-dispersed (skewness = 0.23, kurtosis = −0.79), however, with an IQR of 37.73, this data is driven more by global market forces as opposed to Turkish-specific reasons. The difference between means and medians is pronounced, particularly for the exchange rate (5.98 vs. 2.12) and price level, revealing structural breaks that in all likelihood were associated with the 2018 currency crash and subsequent heterodox policy initiatives. These properties reflect the intrinsically difficult task faced by policymakers in a small, open economy subject to significant variability, that relies heavily on imports, and that is subject to potential external shocks and policy regime changes. Formal structural break tests reported in Section Structural Break Tests confirm this instability. They date a significant break at the currency crisis of 2018M08 and place the dominant regime shift in late 2021.

A remark on the choice of the exchange rate measure is in order. The analysis employs the bilateral nominal TL/USD rate rather than a real or trade-weighted effective index, and this choice follows directly from the theoretical model. Equation (2) defines the domestic price of imported goods as the product of the foreign price level and the nominal exchange rate, so the nominal bilateral rate is the variable that the derivation itself prescribes. A CPI-based real effective exchange rate would be unsuitable in this framework for a mechanical reason: its construction embeds the domestic consumer price index, which is the very variable the models seek to explain, and its inclusion would therefore introduce circularity between regressor and target. In addition, the TL/USD rate is the relevant pricing benchmark in the Turkish context, where import invoicing and financial dollarization are overwhelmingly denominated in US dollars, and the imported cost information that a currency basket would carry is already spanned jointly by the exchange rate (E) and the import price index (P^*) that enter the models as separate predictors. Replicating the analysis with nominal effective or basket measures remains a worthwhile extension, which we leave to future research.

Figure 2 (Histograms) confirms these insights. The histograms reveal distinct distributional patterns across macroeconomic variables during 2003–2024. Oil prices (Z) and foreign price levels (P^*) exhibit near-normal distributions, reflecting stable global dynamics, while most domestic variables show significant departures from normality. The exchange rate (E) and price level (P) display pronounced right skewness, indicating structural breaks likely coinciding with the 2018 crisis and subsequent policy regime changes. Real interest rates (r) exhibit extreme kurtosis (19.73), suggesting the frequent occurrence of extreme values typical of volatile emerging-market conditions. The money supply (M) shows exponential growth patterns characteristic of expansionary monetary policies, while growth rates (y) capture the severe COVID-19 contraction alongside typical business cycle fluctuations. These distributional properties collectively underscore Turkey's transition from relative macroeconomic stability to high volatility regimes.

Figure 3 shows the dynamics of macro variables, signaling relatively well-defined structural breaks in the economic environment of Turkey. The level of foreign exchange rate (E), and price (P) show high stability until 2018 and exponential deterioration until the currency crisis and the adoption of the heterodox policy. Inflation expectations (π^e) began to explode in 2018–2019 and more recently are again spiking, suggesting credibility problems for monetary policy. Real interest rate (r) remains a persistent source of volatility throughout the sample period, with extended periods of parallel rates particularly after 2020, whereas money supply (M) presents a dimensional acceleration in its exponential growth rate since $r = 0$. Oil prices (Z) experienced the same standard pattern of global commodity cycles and have peaks in the 2008 financial crisis and recent geopolitical tensions, confirming their role as an important external source of cost pressures in the inflation dynamics of Turkey.

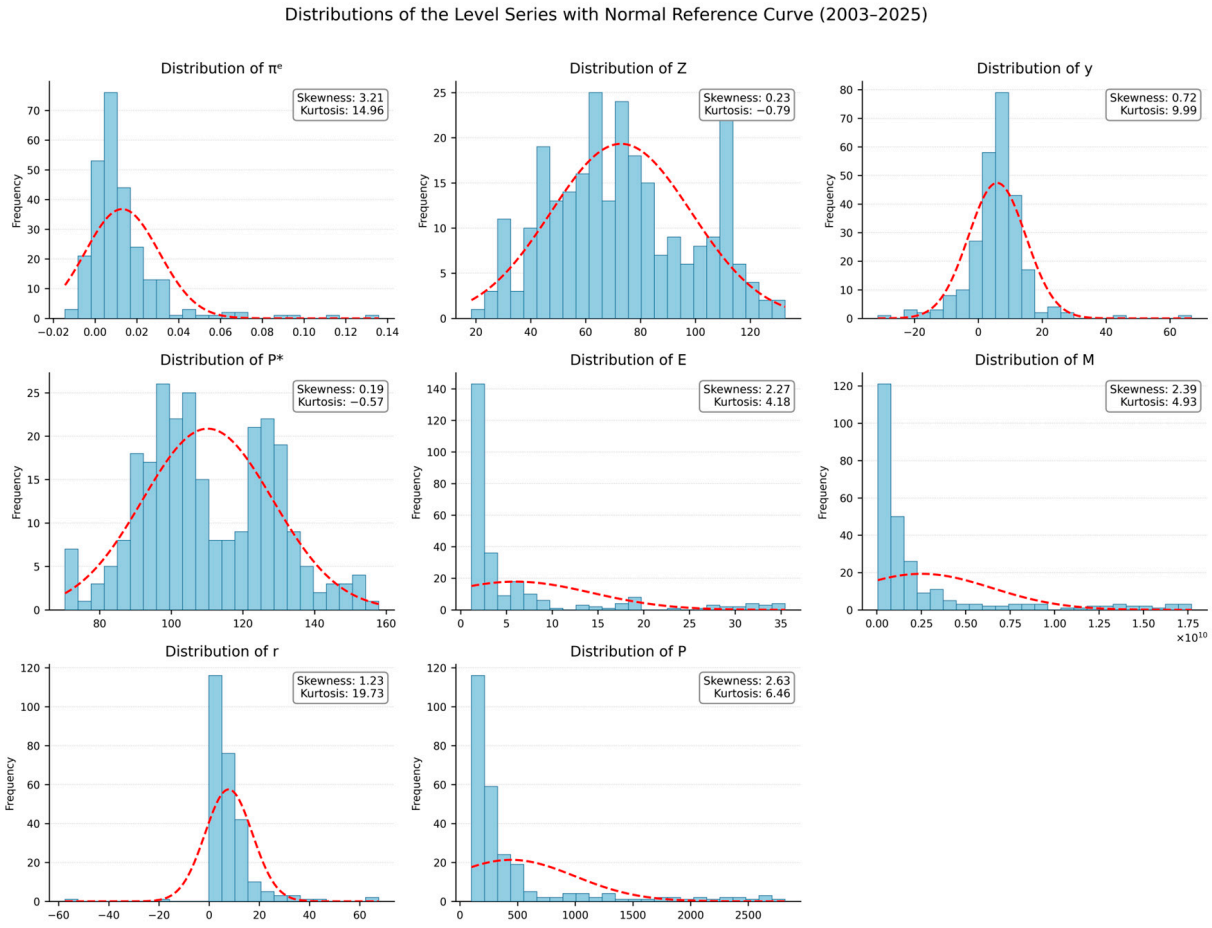

Figure 2. Histograms of the level series with normal reference curves.

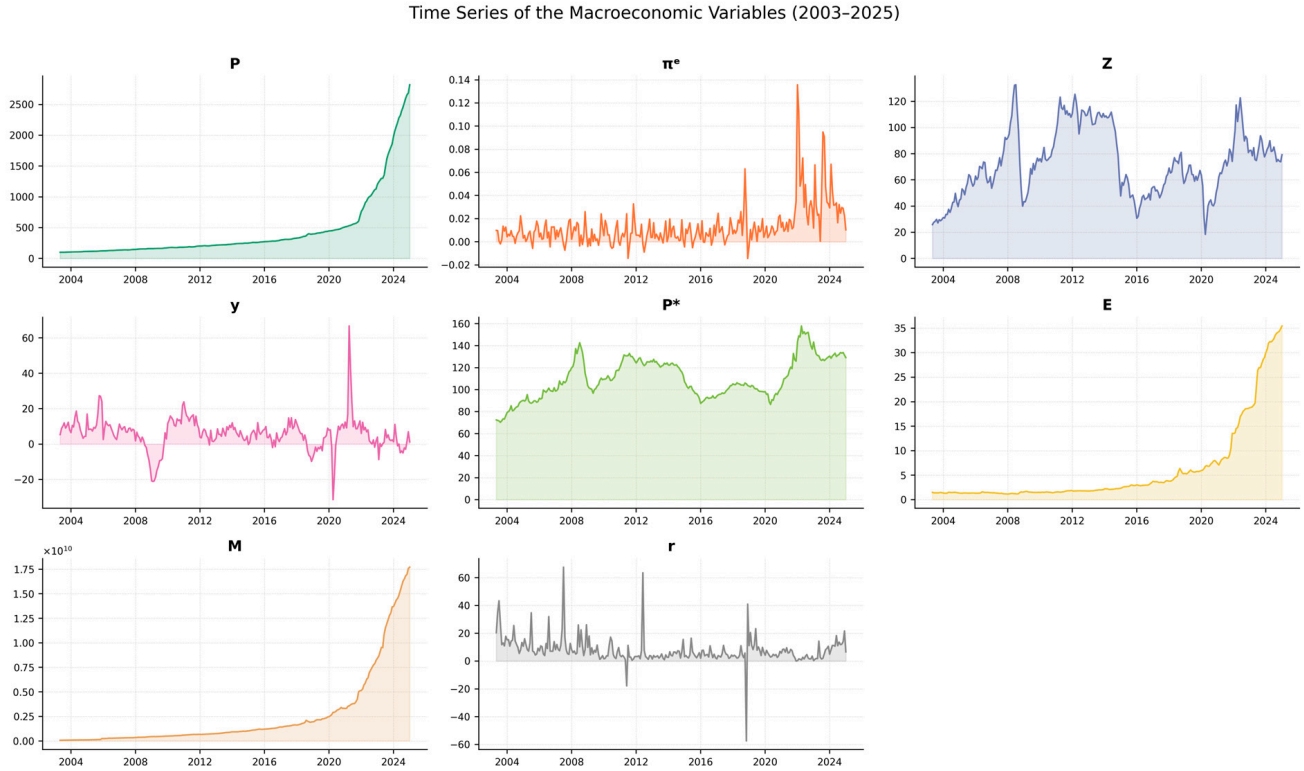

Figure 3. Time series trends.

Figure 4 presents the correlation matrix for the macroeconomic variables. The heatmap displays pairwise Pearson correlation coefficients, with a color gradient ranging from blue (strong negative correlation) to red (strong positive correlation), and numerical values included for precise interpretation. Strong positive correlations are observed among the price level (P), exchange rate (E), and money supply (M), with coefficients of 0.9898, 0.9968, and 0.9958, respectively, indicating a close co-movement among these nominal variables. A notably high correlation between the foreign price level (P^*) and the external variable (Z) (0.8540) also highlights a significant association. In contrast, the interest rate (r) and real output (y) exhibit weak or negative correlations with other variables, possibly reflecting real-side dynamics or the lagged effects of monetary policy.

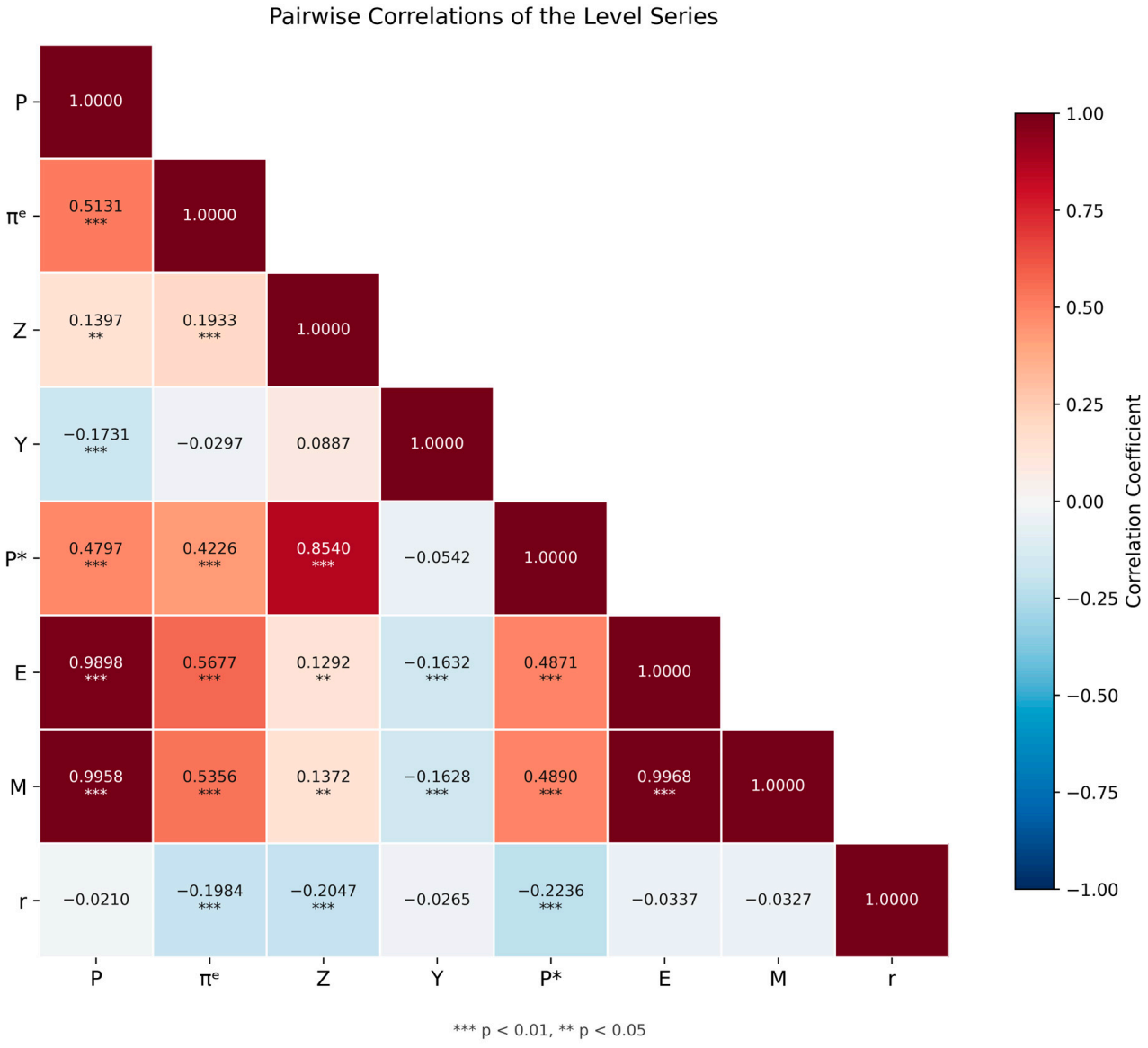

Figure 4. Pairwise correlations of the level series.

The correlation matrix indicates a strong interconnectedness among the macroeconomic variables in the case of Turkey for the period of 2003–2024, drawing attention to emanating role of the exchange rate channel in the process of external shock transmission through to domestic inflation. This strong positive correlation between the exchange rate (E) and domestic price level (P) confirms the high sensitivity of exchange rate pass-through in the Turkish economy, the responsibilities of which are clearly alluded to in the identified

structural frailties recorded in its heterodox policy phase after the year 2017. The relevance of monetary policy credibility in providing price-level-restoring anchors is further supported by the positive relationship between M and P and the negative relationship between r and π^e. The weak correlation between world oil prices (Z) and domestic variables, which indicates the extent of Turkey's vulnerability to external commodity price shocks, is all the more significant in times of energy price instability. These relationships are consistent with those implied by the historical relationship, which stresses that inflation processes in Turkey are ultimately determined by a complex dynamic interaction between ER devaluation, expansionary monetary policy and external price pressures, which must be heavily coordinated in order to give place to a solid macroeconomic stability.

A natural concern raised by Figure 4 is multicollinearity, since the price level (P), the exchange rate (E), and the money supply (M) display pairwise correlations close to 0.99. It should be stressed, however, that these near-perfect correlations are a property of the variables in levels. They reflect the common stochastic trend that nominal series share in a chronically inflationary economy. The models themselves are estimated on rates of change, as specified in Equation (12), and in the transformed dataset, collinearity is negligible. The largest absolute pairwise correlation among the seven predictors is 0.39, observed between oil prices and foreign prices, and the variance inflation factors range from 1.00 to 1.23, far below the conventional threshold of 5. Moreover, the machine learning methods employed in this study do not rely on matrix inversion, which renders ordinary least squares fragile under collinearity, so deep neural networks and random forests remain estimable and predictive even with highly correlated inputs. The main consequence of residual correlation is instead interpretive in nature: correlated predictors can share, and thus dilute, measured feature importance. We explicitly diagnose and discuss this effect in the context of the negative permutation importance values in Section 5.2.

Structural Break Tests

To formally substantiate the structural instability evident in Figures 2 and 3, we subject the series to a battery of structural break tests. First, we apply the multiple breakpoint procedure of Bai and Perron (1998, 2003) to the monthly inflation rate and to the rate of change of the nominal exchange rate. The procedure is based on least squares segmentation with a 15% trimming rule, and the number of breaks is selected by the Bayesian Information Criterion. Second, we compute Chow (1960) tests at three candidate break dates: the shift toward heterodox policies in 2017M01, the currency crisis in 2018M08, and the beginning of the unorthodox rate-cut cycle in 2021M11. These tests use an AR(1) specification for inflation. Third, we run the unit root test of Zivot and Andrews (1992), which allows for a single endogenously determined break. Finally, we inspect the CUSUM of squares statistic for variance stability.

The results, reported in Table 3, formally confirm the presence of structural breaks and refine their timing. The Chow test rejects parameter stability at the currency crisis of 2018M08 with an F statistic of 15.13 and a p-value below 0.001, which corroborates the regime shift emphasized in the historical narrative. At the same time, all three endogenous dating procedures, namely the Bai and Perron segmentation, the Zivot and Andrews test, and the CUSUM of squares statistic, locate the dominant break in late 2021, between 2021M10 and 2021M11. At that point, the average monthly inflation rate rose roughly fivefold, from 0.81% to 4.15%. This date coincides with the unorthodox rate-cut cycle initiated in September 2021 and with the ensuing collapse of the lira in December 2021. The exchange rate series exhibits its own break slightly earlier, in 2021M02. Taken together, the tests indicate that the post-2017 heterodox policy era contains two statistically identifiable episodes of instability: the 2018 currency crisis and, most prominently, the regime shift of late 2021. They therefore

provide formal support for the structural break interpretation maintained throughout the paper. These findings also justify the use of machine learning methods that are robust to regime changes, since linear constant parameter models would be misspecified over the full sample.

Table 3. Structural break test results, 2003–2024.

Test	Series	Statistic/Selection	Break Date(s)
Bai and Perron (BIC)	π (inflation)	1 break; regime means rise from 0.81% to 4.15% (monthly)	2021M10
Bai and Perron (BIC)	ΔE (FX change)	1 break; regime means rise from 0.80% to 3.62% (monthly)	2021M02
Chow	π, AR(1)	F = 13.02 (2017M01); F = 15.13 (2018M08); F = 28.00 (2021M11); all $p < 0.001$	2017M01 / 2018M08 / 2021M11
Zivot and Andrews	π (inflation)	t = -8.30, $p < 0.01$; unit root rejected at break	2021M10
CUSUM of squares	π, AR(1) residuals	max. deviation 0.475 > 0.084 (5% band): instability	2021M10

4. Methodology

CMTSA uses a novel hierarchical structure starting with an advanced DNN architecture that incorporates batch normalization and dropout regularization techniques. As shown in Figure 5, CMTSA encompasses three main stages: data preprocessing, model architecture optimization and evaluation, and causal inference with policy interpretation. First, the data are preprocessed: the series enter the models as rates of change, the sample is split chronologically into training and test sets, the variables are scaled to the unit interval, and the arrays are converted into an appropriate tensor format for deep learning implementation. The modelling task is regression throughout; a binary up-or-down indicator is computed ex post for the calculation of the mean directional accuracy metric and plays no role in estimation. Second, we optimize the DNN architecture by meticulously configuring the neural layers, batch normalization, dropout parameters, and hyperparameter tuning, followed by systematic model training. Third, causal inference is conducted using the DoWhy framework, which enables the estimation of true causal effects of key macroeconomic variables on inflation by constructing a structural causal model, identifying estimands, estimating treatment effects, and performing robustness checks through refutation methods.

Concerning model validation, the dataset is partitioned chronologically into a training set that comprises the first 70% of the sample (182 monthly observations, from 2003M06 to 2018M07) and a held-out set that comprises the final 30% (78 monthly observations, beginning in 2018M08). No shuffling is applied when the sample is split, so the temporal ordering of the data is fully preserved, and every held-out observation postdates every training observation. This design rules out look-ahead bias, in that no future observations enter the training window. The Optuna-based hyperparameter search and the early stopping rule monitor the loss on the held-out window, which therefore also serves as the validation set for model selection, a common practice in small sample macroeconomic applications where a further split would leave too few observations for reliable training. We note that the held-out window deliberately spans the 2018 currency crisis and the post 2021 inflationary episode identified in Section Structural Break Tests, so the reported

metrics describe model performance under regime change, which constitutes a demanding evaluation environment for any forecasting model.

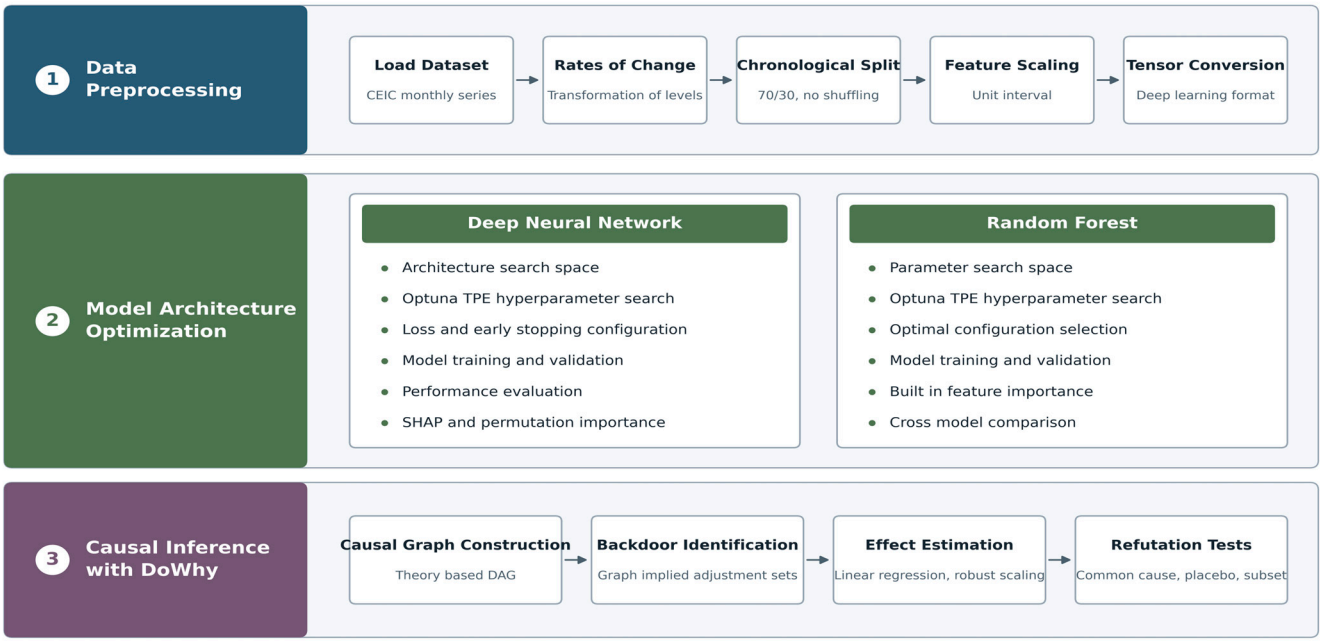

Figure 5. The workflow of the CMTSA framework.

Optimized with tailored hyperparameter combinations, the architecture developed within the CMTSA framework demonstrates a significantly greater capacity to capture nonlinear relationships compared to traditional time series models (Yan et al., 2021; Barongo & Mbelwa, 2024). In parallel with the deep learning implementation, a Random Forest algorithm is employed to validate results and enhance interpretability by ranking the relative importance of inflation determinants. This dual-track modeling approach provides valuable insights into the hierarchical structure of explanatory variables and reinforces the robustness of the empirical findings.

Time-series visualizations derived from model outputs reveal complex, dynamic interactions among macroeconomic variables, particularly highlighting the strong, persistent relationship between monetary growth and inflation. This suggests that both immediate and lagged effects of monetary expansion play a crucial role in inflation dynamics, consistent with the Quantity-Theoretical Inflation Theory.

Overall, the hybrid structure of CMTSA—combining deep learning and ensemble-based machine learning—offers a methodologically rigorous and policy-relevant framework. It effectively captures both linear and nonlinear patterns and delivers interpretable outputs that can inform monetary policy in contexts marked by structural breaks and high volatility.

5. Analysis and Results

Building on the CMTSA framework detailed in the previous section, this section of the study presents the empirical results derived from the sequential implementation of deep neural networks (DNNs), random forest algorithms, and causal inference analysis via DoWhy. The objective is not only to model inflation dynamics but also to identify the hierarchical and causal relationships between key macroeconomic indicators and inflation within the Quantity-Theoretical Inflation Theory framework. The DNN component captures complex nonlinear and interaction effects embedded in Turkish inflation data, while the random forest model provides robustness checks and interpretable decision paths through ensemble learning. Finally, DoWhy is employed to distinguish causality from

correlation, offering a structural interpretation of the predictive findings. Each analytical stage complements the others, enabling a triangulated, multifaceted understanding of Turkey's inflationary process from 2003 to 2024. The analyses begin with the DNN model and its interpretability outputs, then proceed to the random forest structure and its feature importance rankings, and conclude with the results of causal inference estimation.

5.1. Deep Neural Network Analysis

In line with the multi-stage modeling framework outlined in the CMTSA methodology, the deep neural network (DNN) component plays a central role in decoding the structural complexity of inflation dynamics in Turkey. Through its hierarchical architecture—optimized with batch normalization, dropout regularization, and carefully tuned hyperparameters—the DNN model systematically transforms Turkish macroeconomic time series data into a multilayered representation that captures both observable and latent economic relationships.

At the foundational level, the model's shallow layers internalize basic price-setting mechanisms influenced by global commodity prices (Z) and foreign price levels (P^*). As the data propagate through the network, intermediate layers begin to detect interdependent channels among exchange rates (E), money supply (M), and inflation expectations (π^e), representing the core interactions of the monetary transmission mechanism. Deeper layers, meanwhile, capture more abstract macroeconomic linkages, such as the impact of real interest rates (r) and output gaps (y) on domestic price levels (P), thus uncovering the underlying propagation structures often masked in conventional econometric approaches.

This layered learning process allows the DNN to simultaneously evaluate the joint behavior of seven key macroeconomic variables and to identify hidden dependencies, including exchange rate pass-through effects, the credibility of monetary policy, and the diffusion of external shocks. Unlike traditional models constrained by rigid functional form assumptions, this architecture autonomously extracts features and constructs high-dimensional functions that approximate nonlinear and interactive relationships within and beyond the training sample. Such flexibility is particularly advantageous for inflation forecasting in economies like Turkey, where structural breaks, global oil shocks, and shifts in monetary regimes introduce complex and overlapping Dynamics (Zheng et al., 2023). The full range of hyperparameters employed in this modeling process is summarized in Table 4.

Table 4. Hyperparameter configuration space for DNN optimization within the CMTSA framework.

Hyperparameter	Search Range	Step Size	Distribution	Description
Number of Layers	1–3	1	Discrete	Number of hidden layers in the network
Hidden Layer Size	16–64	16	Discrete	Number of neurons per hidden layer
Dropout Rate	0.20–0.50	0.05	Uniform	Regularization parameter to prevent overfitting
Learning Rate	1×10^{-5}–1×10^{-3}	-	Log-uniform	Optimizer step size for gradient descent
Batch Size	16–64	16	Discrete	Number of samples per training batch
Weight Decay	1×10^{-5}–1×10^{-3}	-	Log-uniform	L2 regularization strength
Early Stopping Patience	30 epochs	-	Fixed	Max epochs without improvement on validation
Min Delta	0.001–0.005	0.001	Uniform	Minimum improvement threshold to trigger early stopping
Maximum Epochs	100	-	Fixed	Upper limit on training iterations

The core functions considered for the DNN, namely the activation, optimizer, and loss functions, are summarized in Table 5. We adopted modern activation functions (Swish, Mish, GELU, ELU), which exhibit improved gradient flow and provide smooth and non-monotonic characteristics useful for the optimization of deep networks compared to the traditional ReLU functions. Such smooth gradient flow is particularly valuable in this study because the Turkish inflation data-generating mechanism requires the network to capture substantial nonlinearity. The optimizer ensemble, including AdamW, RAdam, NAdam, and Adafactor is the best-of-class ensemble of adaptive learning rate algorithms with bias correction, weight decay, regularization, and momentum terms for classifying the difficult optimization landscape posed by macroeconomic time series, with varying gradient magnitudes under different economies. The dual loss function (MSE + MAE) approach allows the optimization framework to study various error penalty structures so that MSE focuses on capturing the developments of the larger prediction errors pertaining to the inflation volatility spikes in a more pronounced way, whereas MAE offers robustness against outliers in the case of the 2018 currency crisis and the COVID-19 pandemic shocks in the economy (Kumar, 2022).

Table 5. Core function selection for DNN inflation modeling.

Parameter	Options	Selection Criterion
Activation Function	Swish, Mish, GELU, ELU	Modern functions with smooth gradients
Optimizer	AdamW, RAdam, NAdam, Adafactor	Advanced adaptive learning rate algorithms
Loss Function	MSE, MAE	Suitable for regression tasks

Table 6 reports the optimal hyperparameter configuration together with the corresponding model performance. The Optuna-based hyperparameter-optimization procedure (by default of TPE (Tree Parzen Estimator) sampler) ended up with a parsimonious single hidden-layer architecture with 16 neurons, meaning that the inflation process in Turkey can be represented successfully by relatively simple nonlinear transformations of the seven macroeconomic variables. This model generalizes well to unseen examples, although the R^2 test (0.366) is still better than the R^2 train (0.133), supporting the fact that dropout regularization (0.4) and weight decay (0.000308) prevent the model from memorizing the training patterns. The decline in MAPE from training (189.29%) to testing (86.18%) reflects denominator mechanics explained below, while the improvement in MDA (48.62% to 63.64%) indicates acceptable directional prediction of inflation.

Table 6. Optimal hyperparameter configuration and model performance for the deep neural network.

Category	Parameter	Optimal Value	Performance Metric	Training	Testing
Architecture	Number of Layers	1	**RMSE**	0.008070	0.029899
	Hidden Layer Size	16	**MAPE (%)**	189.29	86.18
Regularization	Dropout Rate	0.4	**MDA (%)**	48.62	63.64
	Weight Decay	0.000308	**R^2**	0.133	0.366
Optimization	Learning Rate	0.000489			
	Optimizer	NAdam			
	Batch Size	24			
Training	Loss Function	MSE			
	Min Delta	0.004			
	Activation Function	GELU			

The optimal configuration favoring NAdam optimizer (with its moderate 0.000489 learning rate) and GELU activation mirrors the complex and non-stationary insiders of Turkish inflation data nourished by empirical experience, where adaptive learning rates and smooth activation functions hedged convergence amidst structural breaks and regime changes characterizing 2003–2024. The apparent paradox that the test R^2 (0.366) exceeds the training R^2 (0.133) deserves an explicit explanation, since readers may otherwise read it as a sign of instability. The R^2 statistic is not comparable across subsamples with different variances. The held-out window contains the high inflation episodes after 2018, so the variance of its target is many times larger than that of the tranquil training window, and a larger absolute error can therefore still translate into a higher share of explained variance; indeed, the test RMSE (0.0299) is almost four times the training RMSE (0.0081). The very high training MAPE is likewise a mechanical artifact of near-zero monthly inflation values in the denominator during the low inflation years that dominate the training window, and it coexists with a small training RMSE precisely for that reason.

The absolute level of the out-of-sample fit deserves a candid assessment. A test R^2 of 0.366 indicates that the network explains roughly one-third of the variance in monthly inflation in the held-out window, and several considerations put this figure in context. First, the target variable is the monthly rate of change of the price index, a series that is intrinsically noisy and much harder to fit than the trending price level, for which spuriously high R^2 values are easily obtained. Second, the held-out window is not a tranquil period. It begins with the currency crisis of 2018M08 and includes the dominant structural break of late 2021 identified in Section Structural Break Tests, so the model is judged primarily on the episodes in which the data-generating process shifted most violently. Third, the very high MAPE values arise mechanically because monthly inflation is frequently close to zero, which inflates percentage errors even when absolute errors are small; the RMSE of about 0.03 corresponds to an average error of roughly three percentage points of monthly inflation in a window where monthly inflation reached almost 14%. Fourth, the model's mean directional accuracy of 63.6% on the held-out window indicates that it retains economically meaningful signal about the direction of inflationary pressure, which is the quantity most relevant for policy. We therefore interpret the DNN's point forecasts with caution and base the paper's substantive conclusions on convergent evidence from feature attribution, ensemble validation, and causal inference, none of which requires a high predictive R2 to be informative. Readers should nonetheless bear in mind that predictive accuracy under regime change remains an open challenge for all forecasting approaches in emerging market settings.

The comparison methodology incorporates two complementary post-hoc interpretability techniques: SHAP (SHapley Additive exPlanations) and Permutation Feature Importance (PFI). SHAP provides a unified framework grounded in cooperative game theory, assigning Shapley values to quantify each feature's individual contribution to specific predictions. This method allows us to answer the question, "How much did feature X contribute to this particular prediction?" by attributing localized effects across output units. In contrast, PFI estimates the global importance of a feature by measuring the drop in model performance when that feature is randomly permuted, thereby addressing "How much worse would the model perform if feature X were excluded?"—albeit without indicating the direction of the effect.

As illustrated in Figure 6, the exchange rate (E) emerges as the most influential predictor under permutation importance (0.65 vs. 0.35), indicating that its perturbation significantly impairs overall model performance. However, SHAP values reveal that its contribution to individual predictions is more nuanced, often mediated through complex interactions rather than direct influence. Meanwhile, foreign price levels (P^*) and world

commodity prices (Z) exhibit diverging patterns: P^* appears relatively unimportant in both global and local contexts, while Z shows higher relevance within SHAP, highlighting its nonlinear interaction effects embedded in deep model structures.

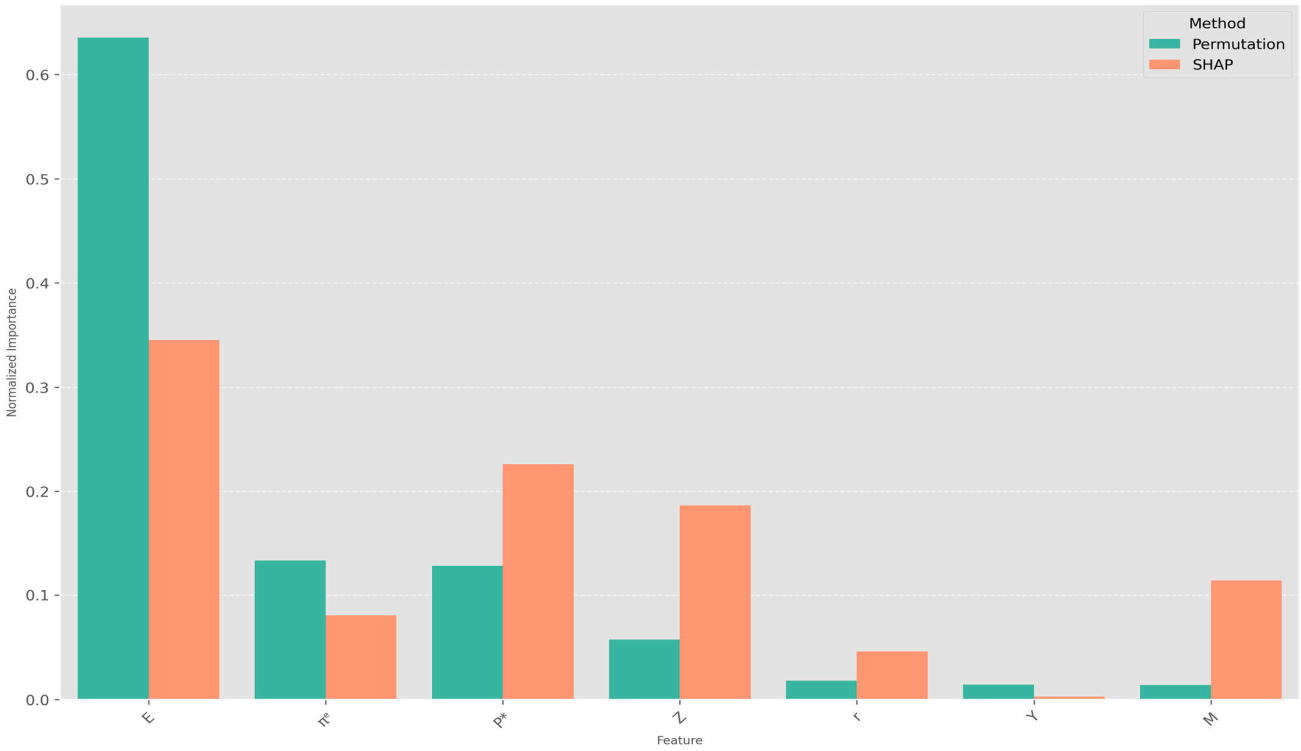

Figure 6. Feature importance comparison: SHAP vs. Permutation methods.

This methodological design underscores the complex nature of variable interdependencies in Turkish macroeconomic dynamics. While exchange rate volatility dominates as the systemic risk transmitter, external price shocks are conveyed through less direct, highly entangled pathways—mechanisms that are more effectively captured by game-theoretic attribution methods such as SHAP. The integration of SHAP and PFI, as visualized in Figure 6, offers a comprehensive understanding of both global feature relevance and local explanatory power—essential for dissecting the multifaceted transmission channels of inflation in Turkey.

5.2. Random Forest Analysis

In the second stage of the CMTSA framework, a random forest algorithm is employed to validate and cross-check the findings obtained from the deep neural network model. This ensemble learning method allows for the identification of the most influential predictors of inflation by averaging across multiple decision trees, thereby enhancing model robustness and interpretability. Unlike the DNN, which captures complex nonlinear interactions implicitly, the random forest approach provides transparent, rule-based insights into how different macroeconomic variables contribute to inflationary pressures. The following subsections detail the hyperparameter optimization process, model performance metrics, and feature importance rankings obtained from the random forest model. The hyperparameter search space and the categorical settings are presented in Tables 7 and 8, the optimal configuration and model performance in Table 9, and the feature importance rankings in Table 10.

Table 7. Random forest hyperparameter optimization framework.

Hyperparameter	Search Range	Step Size	Distribution	Description
N Estimators	50–500	1	Discrete	Number of trees in the forest
Max Depth	5–50	1	Discrete	Maximum depth of individual trees
Min Samples Split	2–20	1	Discrete	Minimum samples required to split an internal node
Min Samples Leaf	1–10	1	Discrete	Minimum samples required to be at a leaf node
Bootstrap	True, False	-	Categorical	Whether bootstrap samples are used for tree building

Table 8. Categorical hyperparameters.

Parameter	Options	Selection Criterion
Max Features	sqrt, log2, None, 0.3, 0.5, 0.7, 0.9	Feature subset selection for optimal splits

Table 9. Optimal hyperparameter configuration and model performance for the random forest.

Category	Parameter	Optimal Value	Performance Metric	Training	Testing
Tree Structure	Number of Estimators	134	RMSE	0.003692	0.030996
	Max Depth	35	MAPE (%)	83.46	85.06
Splitting Criteria	Min Samples Split	12	MDA (%)	91.16	77.92
	Min Samples Leaf	5	R^2	0.763	0.468
Feature Selection	Max Features	0.7 (70%)			
Ensemble	Bootstrap	False			

Table 10. Feature importance analysis: Built-in vs permutation comparison with tree-level insights.

Feature	Built-In Importance	Permutation Impact (%)	Tree #1 Role	Ranking Consensus
r	0.472	1.30	Secondary splits (dominant)	Primary Driver
π^e	0.249	2.82	Root node criterion	Foundational Variable
E	0.118	2.32	Absent (ensemble effect)	Tertiary Driver
M	0.053	−0.35	Deep node (localized)	Weak Influence
P^*	0.051	−1.21	Deep node (marginal)	Weak Influence
Z	0.037	−2.01	Not present	Minimal Impact
Y	0.020	−0.11	Not present	Minimal Impact

The differences in feature importance measures in Deep Neural Networks and Random Forest algorithms indicate fundamental architectural differences between the two models in how they compute relationships in macroeconomic data patterns and variable dependencies. The ensemble-based model (i.e., Random Forest) uses the bootstrap aggregation to sample at the node level as well as the feature-level sampling, and DNN adopts hierarchical representation learning that achieves the multi-layer nonlinear transformation and allows for the automatic feature extraction and non-linear interaction learning (Ravindran et al., 2021).

Tree-Level Analysis and Ensemble Aggregation Dynamics: The visualization of Tree #1 (Figure 7) is highly informative about the hierarchy of decision-making in the Random Forest ensemble: it shows how the feature space is partitioned at each split using a binary recursion. The tree model also clearly shows that inflation expectations (π^e) is the top-level root node criteria ($\pi^e \leq 0.183$) that partitions observations into distinct (inflationary) regimes before other monetary policy variables are brought into the decision path. This

result supports the behavioral macroeconomic theory, which claims that expectation formation is the basis on which other macroeconomic variables pass their influences on to price evolution (Rötheli, 2020).

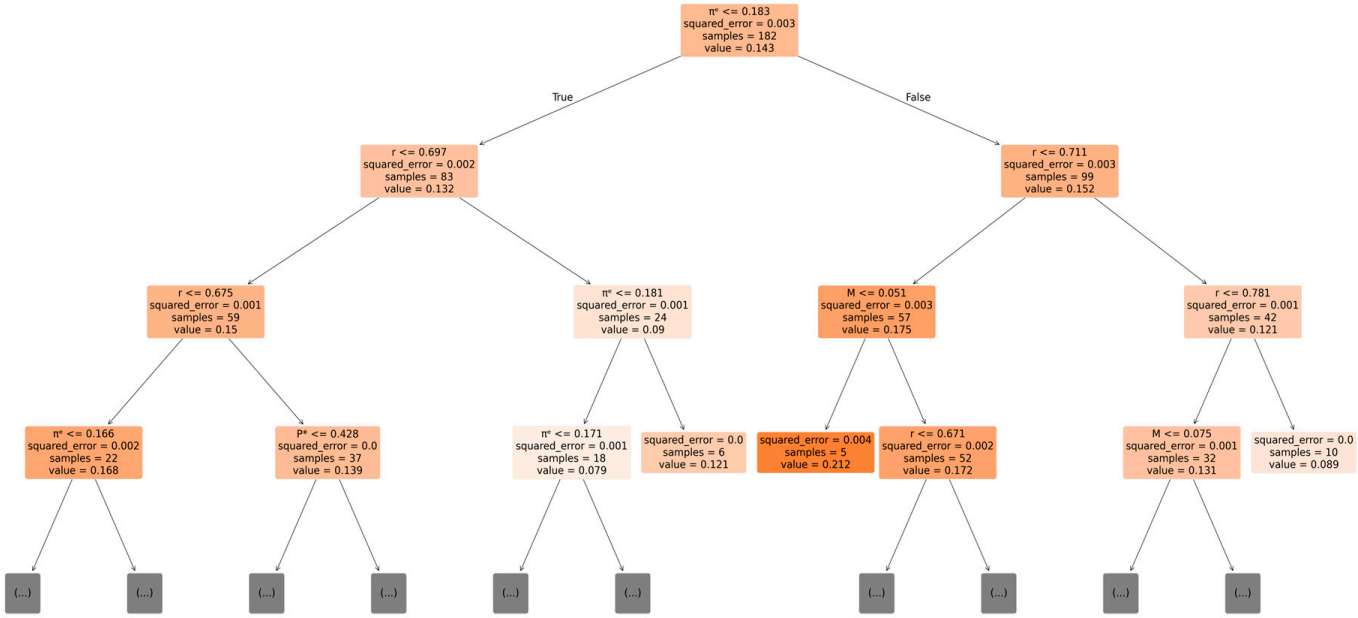

Figure 7. Random forest model—Tree #1.

Algorithmic Feature Selection Mechanisms: The relatively higher prominence of r as compared to E for random forest's built-in importance rankings (47.2%) versus DNN SHAP and permutation analyses serves as a reflection of structural bias within the algorithms when it comes to information gain calculations. The second-level partition of the tree always employs levels of real interest rates ($r \leq 0.697$ and $r \leq 0.711$) to support the efficacy of the transmission mechanism of the CBRT in various expectational regimes. Specifically, the Gini impurity criterion used in Random Forest has a bias toward continuous covariates with high variance and strong univariate predictive power, and the gradient-based optimization approach employed in DNN could help capture the potential interaction mechanism between exchange rate dynamics and other macroeconomic factors (latent).

Bootstrap Sampling and Information Redundancy: The counterintuitive negative permutation effects found in oil prices (Z: −2.01%), in foreign prices (P: −1.21%), and in money supply (M: −0.35%) transmit complex patterns of redundancy due to the presence of multicollinear dependence relationships and parallel transmission. The fact that the money supply ($M \leq 0.051$) and foreign prices (P) variables are used by the tree at deeper nodes illustrates how individual trees can consider apparently irrelevant variables when they contribute only marginal gains in information for different data partitions. This is because the tree acts on a bootstrapped sample, where features are subsampled as max_features = 0.7, making the optimization take place in suboptimal conditions where globally less important variables contribute to the reduction of within-node heterogeneity.

For readers who are less familiar with machine learning diagnostics, the meaning of a negative permutation importance deserves a brief intuitive explanation. Permutation importance is computed by randomly reshuffling the values of one predictor while leaving all other predictors intact and then measuring how much the prediction error of the fitted model increases. If the predictor carries unique information, destroying it in this way must worsen the forecasts, and the importance is positive. A value near zero indicates that the model can compensate for the loss, because the same information is available through

correlated predictors. A negative value, which appears counterintuitive at first sight, simply means that the forecasts became marginally more accurate after the reshuffling.

This outcome arises from sampling noise in a finite test window and from redundancy among correlated predictors, as documented in Section 3: when oil prices, foreign prices, and the money supply transmit their influence largely through the exchange rate and expectations channels, the trees that occasionally rely on them add noise rather than signal in the held-out period. A negative permutation importance, therefore, does not mean that the variable is economically irrelevant or that it harms the inflation process. It means that, conditional on the other predictors already in the model, the variable contributes no additional out-of-sample predictive power. The causal analysis in Section 5.3 addresses the distinct question of whether these variables matter structurally and shows that they do through indirect transmission channels.

Ensemble Heterogeneity and Collective Intelligence: The fact that there are no exchange rate (E) variables in Tree #1 (even though they are the third most important when you aggregate feature importance 0.118), demonstrates how bagging and feature selection can work in the ensemble. This difference is a manifestation of the fact that the algorithm is able to create assorted tree structures with different subsets of variables, which can provide similar predictive capacity, indicating that foreign exchange effects are carried out more prominently in other trees in the 134-tree ensemble by other combinations of pathways. The bootstrap sampling and feature randomization operations of the algorithm allow for reducing the variance of the model while having the ability to navigate through a variety of solution paths. This characteristic of Random Forest has been demonstrated across different datasets and feature selection scenarios (Chen et al., 2020).

Methodological Synthesis and Hybrid Architecture Implications: These algorithmic differences illustrate complementary analytical strengths where Random Forest is good at finding direct, interpretable causal pathways (in transparent tree trunk-branch structures), whilst DNN is able to capture interaction structures and regime-dependent nonlinearities (in learnt representations). That trees work well as individuals for a range of factors, but important ranks are robust across the ensemble, is evidence of how bagging can combine complementary information. Such architectural elements would be particularly useful in macroeconomic settings of model uncertainty and regime switching, where such variable relationships may have time-varying coefficients and structural breaks, with individual trees specializing in different temporal regimes, while ensemble methods that fuse both approaches could leverage Random Forest's interpretable feature selection mechanisms and DNN's complex pattern detection abilities.

5.3. Causality Analysis

The causal analysis is specified as follows. The assumed causal graph shown in Figure 8 contains 8 nodes and 11 directed edges. Seven edges run directly into inflation, one from each explanatory variable, reflecting the reduced form inflation Equation (12). Four additional edges encode structural relationships among the predictors that follow from the theoretical model of Section 2: money growth affects the real interest rate (M to r), the real interest rate affects output growth (r to Y), output growth affects oil demand and hence oil prices (Y to Z), and exchange rate movements affect import prices in domestic currency (E to P^*). In each estimation, one explanatory variable serves as the treatment, and the monthly inflation rate (P) is the outcome, while the remaining variables enter the backdoor adjustment set implied by the graph. The identified estimand is the backdoor adjustment formula, and the effects are estimated by linear regression on robust scaled data, in which every variable is centered at its median and scaled by its interquartile range. This scaling is appropriate for the heavy-tailed distributions documented in Section 3, and

it fixes the units of measurement: each estimate measures the change in inflation, expressed in interquartile range units, that is caused by an interquartile range increase in the treatment variable. Consistent with the adaptive expectations assumption of Equations (5) and (6), in which a lambda of one collapses expected inflation to lagged inflation, expectations enter the causal model in level form.

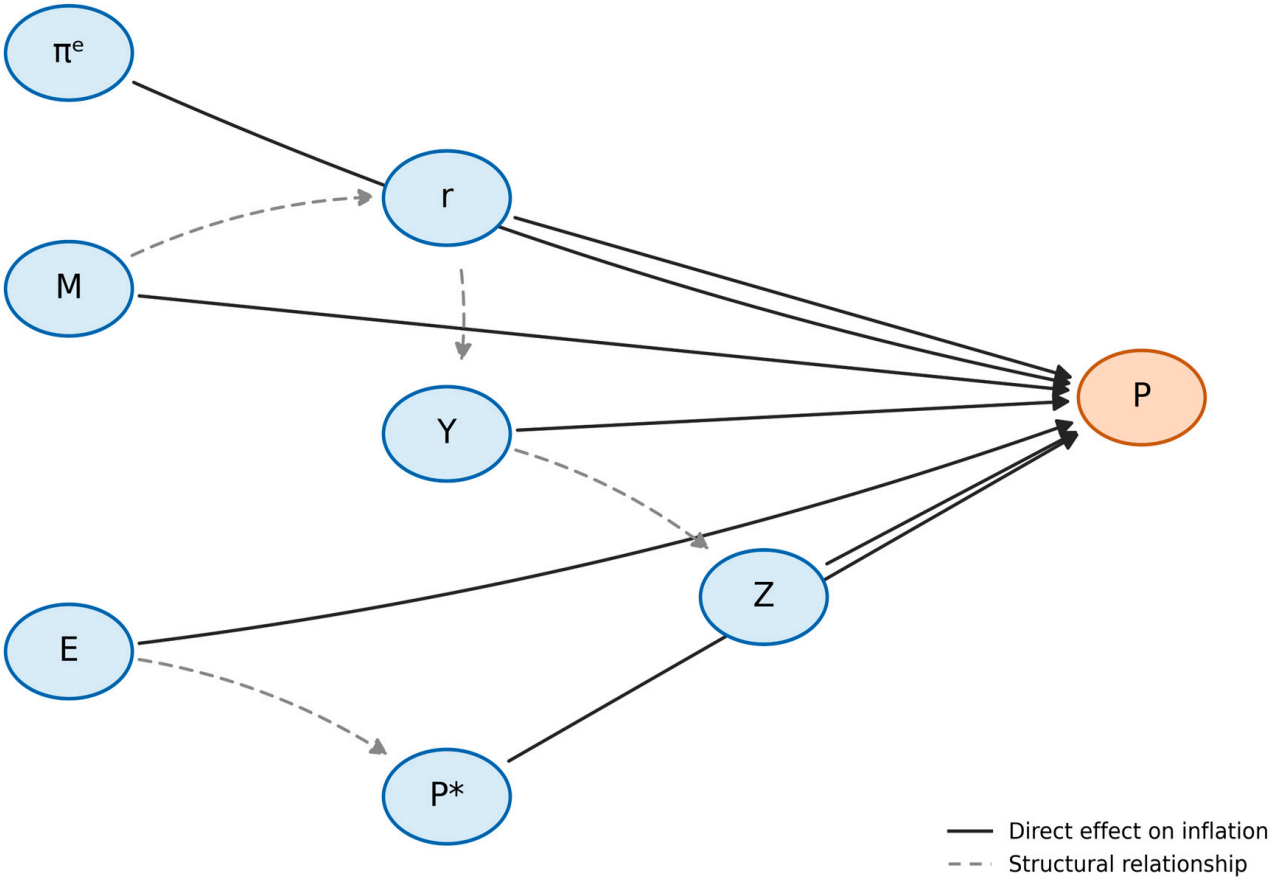

Figure 8. The assumed causal graph of the inflation process.

The estimates, displayed in Figure 9, assign the strongest causal effect to inflation expectations (+0.645, $p < 0.001$), followed by the nominal exchange rate (+0.393, $p < 0.001$) and the foreign price level (+0.274, $p < 0.01$). The real interest rate exerts a statistically significant negative effect (−0.213, $p < 0.001$), providing direct causal evidence that positive real rates restrain inflation and lending empirical support to the policy normalization advocated in the conclusion. Conditional on the expectations level and the exchange rate, the remaining variables are statistically insignificant: oil prices (+0.174), money growth (+0.014), and output growth (−0.028). The insignificance of money growth conditional on expectations and the currency confirms the interpretation maintained throughout the paper: monetary expansion transmits its inflationary impulse indirectly, through the expectations and exchange rate channels, rather than through a contemporaneous direct link. The dominance of the expectations level is the causal counterpart of the inflation persistence documented by the structural break tests of Section Structural Break Tests, and it accords with the central role that the random forest assigns to expectations at the root of its decision trees. The rate of change of expectations, by contrast, is a far noisier object and carries no significant linear causal effect, which explains why the machine learning models, which can exploit its nonlinear spikes, rank it highly in predictive terms, while the linear causal estimator does not.

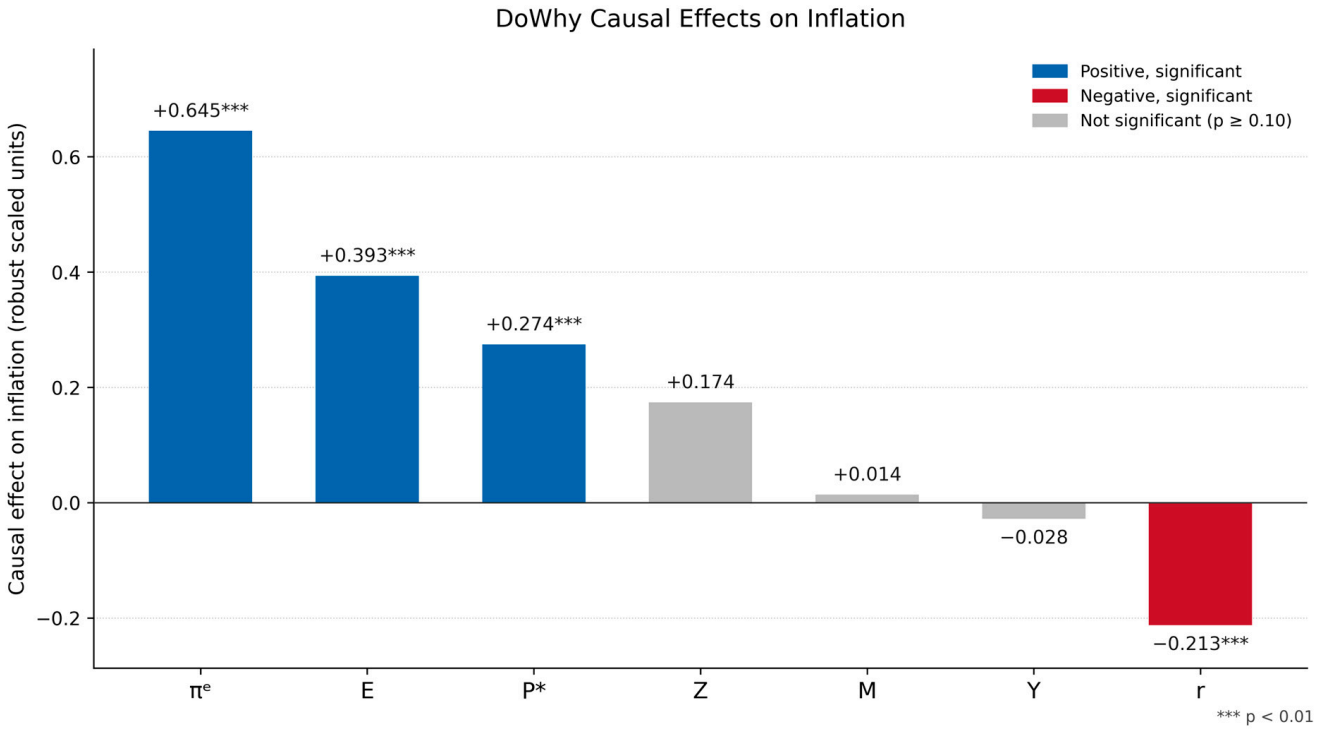

Figure 9. DoWhy causal effects on inflation (robust scaled units).

Three robustness layers support these estimates. First, the refutation battery reported in Table 11 shows that every significant estimate survives the addition of a randomly generated common cause essentially unchanged, collapses toward zero when the treatment is replaced by a random placebo, and remains stable when the model is re-estimated on random 80% subsets of the data; none of the refutation tests rejects the estimates. Second, the results are not an artifact of the scaling choice: re-estimating the model on standardized data preserves the ordering and the significance pattern of all effects. Third, the results are not an artifact of the sparsity of the assumed graph: augmenting the DAG with three theoretically plausible edges, from the real interest rate to the exchange rate through the interest parity channel, from money growth to the exchange rate through the liquidity channel, and from expectations to the exchange rate through dollarization demand, leaves every conclusion intact, with the expectations effect at +0.654, the exchange rate at +0.473, the foreign price level at +0.401, and the real interest rate at −0.137, all significant at the 1% level. All computations use a fixed random seed and are fully reproducible.

Table 11. DoWhy refutation test results (fixed random seed, 100 simulations per test).

Treatment	Effect (p Value)	Random Common Cause	Placebo Treatment	Data Subset (80%)
π^e	+0.645 (<0.001)	+0.645 (0.80)	+0.001 (1.00)	+0.638 (0.90)
E	+0.393 (<0.001)	+0.393 (0.94)	+0.007 (0.90)	+0.369 (0.70)
P^*	+0.274 (0.006)	+0.275 (0.88)	−0.007 (0.90)	+0.277 (0.90)
r	−0.213 (<0.001)	−0.212 (0.98)	+0.009 (0.96)	−0.227 (0.68)
Z	+0.174 (0.447)	+0.174 (0.92)	−0.006 (0.94)	+0.163 (0.88)
M	+0.014 (0.296)	+0.014 (1.00)	+0.001 (0.98)	+0.033 (0.82)
Y	−0.028 (0.101)	−0.028 (0.90)	+0.000 (0.86)	−0.018 (0.68)

Note: Refutation columns report the new effect after each perturbation, with the refutation p value in parentheses; high p-values indicate that the test does not refute the estimate.

6. Conclusions

This study re-examined the determinants of inflation in Turkey using a comprehensive machine-learning-based approach rooted in the Quantity-Theoretical Inflation Theory (QTIT). By employing a Composite Machine Learning Time Series Analysis (CMTSA) framework—integrating Deep Neural Networks (DNNs), Random Forest algorithms, and the DoWhy causal inference toolkit—the study uncovers nuanced dynamics that conventional linear models often fail to detect. The findings of this research not only reaffirm monetarist perspectives on inflation but also provide novel insights into the role of nonlinear interactions, regime shifts, and expectation-driven mechanisms in shaping inflation trajectories in an emerging market context.

One of the central findings is that inflation expectations and the nominal exchange rate are the most powerful and consistent predictors of inflation in Turkey. This result is confirmed across all methodological pathways—DNN interpretability via SHAP, Random Forest feature importance, and DoWhy's causal treatment effect estimates. The prominence of expectations aligns with behavioral macroeconomic theories and the New Keynesian Phillips Curve (NKPC), which emphasizes the forward-looking nature of price-setting behavior. In Turkey's case, especially during the post-2017 heterodox policy period, weakened policy credibility and frequent shifts in the policy regime appear to have unanchored expectations, amplifying inflation's volatility and persistence. This expectation channel is further exacerbated by exchange rate instability, whereby lira depreciation rapidly translates into higher domestic prices through imported input costs and foreign currency-denominated liabilities.

We state this claim with an appropriate qualification: the precise ranking of predictors is model dependent. The random forest attributes the largest built-in importance to the real interest rate, at 47.2%, whereas the SHAP attribution of the network and the causal estimates favor expectations and the exchange rate. What is robust across methods is therefore not a single ordering but the joint prominence of expectations and the exchange rate, and it is on this shared signal that our conclusions rest. An important caveat attaches to this central result. In the absence of long survey-based series, expectations are proxied by lagged inflation under the adaptive expectations assumption of Section 2, so the expectations channel and the intrinsic persistence of inflation are empirically intertwined, and the strength of this channel should be read as evidence on the backward-looking component of expectation formation. The survey-based extensions suggested below therefore remain an important avenue for validating this result.

Monetary expansion emerges as another critical determinant. Although Random Forest models downplay their importance relative to expectations and interest rates due to algorithmic bias against collinear variables, the DNN and theoretical derivations strongly support their dominant role. This reinforces the core proposition of QTIT that inflation is "always and everywhere a monetary phenomenon" (Friedman, 1994). The high correlation between money supply growth and inflation, as well as the temporal alignment of monetary loosening with inflation spikes, underscores the inadequacy of unconventional monetary experiments—such as rate cuts in the face of rising inflation—in containing price level increases in Turkey. The causal estimates sharpen this interpretation. Conditional on the expectations level and the exchange rate, the direct contemporaneous effect of money growth on inflation is statistically insignificant, which is precisely what one expects when monetary expansion operates through the expectations and currency channels rather than through an immediate direct link.

Real interest rates also play a significant role, particularly as mediators of the monetary transmission mechanism. The Random Forest analysis consistently identifies real interest rates as critical splitting nodes in decision trees, suggesting their role in influencing

expectations and aggregate demand. However, their impact appears asymmetric and nonlinear; during some periods, especially under negative real interest rate regimes, they fail to suppress inflation expectations, likely due to diminished credibility of the policy stance. The causal analysis adds direct evidence on this point: the estimated effect of the real interest rate on inflation is negative and statistically significant (-0.213 in robust scaled units), which confirms that positive real returns restrain price growth.

Interestingly, global oil prices, while theoretically relevant, exhibit weak conditional effects on domestic inflation in both the machine learning models and the causal analysis. Foreign price levels behave differently: the causal estimates attribute to them a significant direct effect ($+0.274$ in robust scaled units), the third-strongest in the system, in line with the import-cost channel of the theoretical model. Nevertheless, the impact of oil prices becomes more salient when considered through indirect channels—mainly exchange rates and expectations. In a highly import-dependent and energy-insecure economy like Turkey's, the pass-through of global cost shocks to domestic inflation depends on currency valuation and the overall monetary policy stance. Hence, even though the conditional statistical contribution of oil prices appears marginal, their economic relevance cannot be dismissed, particularly in an open economy context.

In comparing these findings with existing literature, the results generally support the view that Turkey's inflation is structurally anchored in monetary variables and exchange rate pass-through, consistent with studies by Yilmazkuday (2022), Saygılı (2023), and Kocoglu (2023). However, the integration of machine learning reveals more intricate dynamics. For instance, expectations are often treated as residual components in structural VAR models or omitted entirely in traditional analyses due to data limitations. In contrast, this study explicitly and rigorously quantifies their causal power. Moreover, by identifying the feedback loops between expectations, monetary policy instruments, and inflation, it contributes to the growing literature on credibility and central bank communication in inflation-targeting regimes.

Another novel contribution lies in highlighting the nonlinear and regime-dependent nature of inflation determinants. The hybrid CMTSA architecture captures how variable importance shifts across policy regimes—for example, during the 2002–2016 period of inflation targeting versus the 2017–2024 era of heterodox experimentation. Such transitions are difficult to model with classical time-series approaches that assume stable parameters or stationarity. This further justifies the use of data-driven models capable of learning from structural breaks and endogenous changes in macroeconomic behavior.

From a policy perspective, the findings of this research have several important implications. First and foremost, restoring the credibility of monetary policy must be a top priority. Inflation expectations are found to be the strongest causal driver of actual inflation; as such, credible forward guidance and consistent policy actions are vital. This requires re-establishing central bank independence, refraining from political interference, and transparently communicating the monetary policy stance to the public.

Second, policy normalization toward orthodox frameworks—particularly inflation targeting with positive real interest rates—is essential. The study clearly demonstrates that negative real interest rates, combined with rapid money supply growth, have led to inflationary spirals. Reinstating real returns on lira-denominated assets would help anchor expectations, stabilize capital flows, and support currency valuation, thereby reducing imported inflation.

Third, exchange rate management should be an integral part of inflation control. Although a floating exchange rate regime is theoretically desirable, in the context of shallow financial markets and high dollarization, passive currency depreciation feeds inflation through both expectations and import channels. Therefore, the central bank should strengthen its reserve position and consider targeted interventions to prevent disorderly currency movements.

Fourth, reducing reliance on fiscal-monetary coordination for deficit financing is crucial. Although not the primary focus of this study, the historical context reveals that inflationary episodes in Turkey have often been associated with fiscal dominance and monetization of debt. Strengthening fiscal discipline and reducing quasi-fiscal expenditures can help alleviate the inflationary burden on monetary authorities.

Fifth, improved data transparency and monitoring of inflation expectations are needed. Currently, expectations are proxied using backward-looking indicators due to the limited availability of survey-based or market-implied measures. Developing such tools can enhance real-time policy evaluation and guide better decision-making.

Finally, for future researchers, this study opens several pathways. Incorporating real-time data and forward-looking variables such as inflation-indexed bond yields or consumer surveys could improve expectation modeling. Additionally, extending the CMTSA framework to include geopolitical risks, supply chain disruptions, or political uncertainty indices may offer a more holistic view of inflation dynamics. Sectoral disaggregation—such as analyzing inflation in tradable vs. non-tradable sectors—could also reveal the distributional impact of monetary policy. Comparative studies using similar frameworks in other emerging markets may further validate the generalizability of these findings and refine our understanding of inflation under varying institutional conditions. A further natural extension is to replicate the framework with alternative exchange rate measures, such as the nominal effective rate or a trade-weighted basket, in order to verify that the dominance of the exchange rate channel does not hinge on the bilateral TL/USD definition adopted here on theoretical grounds.

In conclusion, this research demonstrates that advanced analytical methods can meaningfully contribute to macroeconomic policy formulation, particularly in complex, high-volatility environments. Turkey's inflation story is not simply about monetary expansion or external shocks, but about the interplay of expectations, credibility, and institutional integrity. Addressing inflation sustainably thus requires a holistic approach—grounded in empirical rigor, theoretical clarity, and consistent policy action.

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